Application of Artificial Intelligence and Machine Learning in the Automation of Supply Chain

تطبيق الذكاء الاصطناعي والتعلم الآلي في أتمتة سلسلة التوريد

by

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Abstract

The current study was conducted by means of a quantitative research design with the focus being that of the application of artificial intelligence and machine learning in terms of supply chain automation. Herein, the author focused on investigating supply chain-based automation trends, evaluating the type of supply chain outcomes that technologies such as machine learning and artificial intelligence lead to, and the type of technologies that lead to improvements in the supply chain. For this purpose, the author had made use of a suitably large sample size of one hundred and eighty-five participants. These participants were sent an online survey questionnaire comprised of five demographic questions and fourteen survey question items. This allowed the author to find that machine learning is highly prevalent in the UAE's supply chains with artificial intelligence being specifically lacking. Through the findings, it was concluded that this may be due to the fact that artificial intelligence currently remains as a developing technology that needs to be furthered greatly in order to be relevant in the current supply chain environment. Lastly, the author was able to recommend that supply chains should integrate technologies that combine with the human effort rather than focus on replacing them.

Keywords: Automation, Supply Chain, Machine Learning, Artificial Intelligence, UAE, and Value Creation

Abstract in Arabic

أجريت الدراسة الحالية عن طريق تصميم بحث كمي مع التركيز على تطبيق الذكاء الاصطناعي والتعلم الآلي من حيث أتمتة سلسلة التوريد. هنا ، ركز المؤلف على التحقيق في اتجاهات الأتمتة القائمة على سلسلة التوريد ، وتقييم نوع نتائج سلسلة التوريد التي تؤدي إليها تقنيات مثل التعلم الآلي والذكاء الاصطناعي ، ونوع التقنيات التي تؤدي إلى تحسينات في سلسلة التوريد. لهذا الغرض ، استفاد المؤلف من حجم عينة كبير مناسب من مائة وخمسة وثمانين مشاركًا. تم إرسال استبيان استبيان إلى هؤلاء المشاركين عبر الإنترنت يتكون من خمسة أسئلة ديموغرافية وأربعة عشر عنصرًا من أسئلة الاستبيان. سمح ذلك للمؤلف باكتشاف أن التعلم الآلي منتشر بشكل كبير في سلاسل التوريد في الإمارات العربية المتحدة مع الافتقار إلى الذكاء الاصطناعي على وجه التحديد. من خلال النتائج ، تم التوصل إلى أن هذا قد يرجع إلى حقيقة أن الذكاء الاصطناعي لا يزال حاليًا كتكنولوجيا متطورة تحتاج إلى مزيد من التعزيز من أجل أن تكون ذات صلة ببيئة سلسلة التوريد الحالية. أخيرًا ، كان المؤلف قادرًا على التوصية بضرورة أن تدمج سلاسل التوريد التقنيات التي تتحد مع الجهد البشري بدلاً من التركيز على استبدالها.

الكلمات الرئيسية: الأتمتة ، سلسلة التوريد ، التعلم الآلي ، الذكاء الاصطناعي ، الإمارات العربية المتحدة ، وخلق القيمة

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Table of Contents

List of Figures

CHAPTER ONE: INTRODUCTION TO THE RESEARCH

Currently, artificial intelligence is more accessible than it has ever been. Moreover, it is now being increasingly incorporated to enhance business outcomes and operations in fields such as retail, healthcare, finance, logistics, and transportation management as well as many more. A study by Baryannis, *et al*., (2019) showed that several organizations are currently researching artificial intelligence-based solutions and automations with nearly half of which attempting to implement said automations and solutions. In simplistic terms, this technology allows organizations to segment large data quantities into identifiable information that can aid the making of quick and informed business decisions. For management in supply chains, this technology is currently being used for its intelligence alongside machine learning, its companion technology, to attain improved performance visibility and higher efficiency in processes to lead toward impactful bottom line bolstering changes (Baryannis, *et al.*, 2019).

1.1.Research background

COVID-19 has placed a considerable amount of pressure on various industries, including supply chains. However, it has brought along with it a silver lining – a chance for change. As companies are now forced to work in ways that are smarter to meet the needs and expectations of customers, there exists the need to leave behind legacy and inefficient investments and tools to focus more so on tools and processes that are efficient. Utilizing machine learning and artificial intelligence to challenges posed by the pandemic can act as the crucial differentiator behind reduced and improved supply chain growth. These technologies, when correctly used, can enhance logistic visibility, aid the successful automation of processes, and provide planning insights that are driven by data (Pandian, 2019).

Machine learning and artificial intelligence have, similar to any promising and developing technologies, been misrepresented or exaggerated about as causing unforeseen challenges (Pandian, 2019). Organizations in the logistics industry have to be diligent and prudent in considering how and when these technologies can be introduced into their operations. In particular, these useful and powerful tools can have their potential hindered by overengineered processes, complex instruments, and panicked data scientist hirings. Rather, companies should focus on investing time in learning about these technologies and the manner in which they are providing adopters with success.

With regards to the agility a company has when faced with uncertainty and opportunities, cost control, and the experiences of the customer, supply chains have a critical part to play. Organizations look toward traceability, reliability, and speed whilst taking their inventory optimization, deadlines, and cost incentives into consideration (Awan, *et al.*, 2021). Managers of supply chains have to avoid incidents and monitor factors that may interrupt the process of supply – primarily from general incidents such as defects in quality and delays in delivery to major incidents such as financial instability on the supplier side, natural disasters, political instability, etc. Each of these can lead to complexities in the chain of supply in environments that are uncertain already. Awan, et al. (2021) state that a chain of supply is an organization network that is involved across downstream and upstream connections, in various activities and processes that lead to value in the form of services and products being provided to the end customer.

In order to work well in the complicated environment that they tend to operate as well as to develop chains of supply that are resilient and agile, these connections, activities, and processes necessitate optimization, prediction, forecasting, and monitoring. Recently, the world has seen a number of AI-based applications be developed for various different disciplines including chains of supply (Plastino & Purdy, 2018). This technology allows systems to automatically execute duties and make decisions that are resourceful without the need for human intervention. Organizations utilize machine learning as well as artificial intelligence to attain insight into several domains including the management of the chain of supply, logistics, and warehousing.

Although the definition of artificial intelligence differs based on the perception that one has of it, a restriction definition could include every tool and machine that is able to mimic the intelligence of humans by utilizing computational capabilities (Plastino & Purdy, 2018). AI allows for the implementation of predictive approaches that aid quick evaluations and effectively minimize disruptive and risky events that can take place across the chain of supply. It also allows users to find chain of supply patterns that emerge thereby developing models to easily assess the working of a process and finding possible inefficiencies therein (Plastino & Purdy, 2018). Artificial intelligence, in this approach that allows for the finding of inefficiencies and improvements to the chain of supply, is able to offer organizations with the ability to constantly learn about areas that can be improved, anticipate performance, and find performance affecting factors.

In the context of the chain of supply, artificial intelligence acts as an innovation that has a great deal of potential that is yet to be entirely and clearly comprehended. The overall literature available on the matter is restricted with regards to this technology's application in the field of supply chain and the study will focus on evaluating and providing an extensive perspective of this technology's application with regard to chains of supply that will act as a reference for future practitioners and researchers.

1.2.UAE logistics industry

The United Arab Emirates' logistics and freight market is one that, in 2020, was valued at about seventeen billion dollars with its value expected to surpass thirty billion in the coming years through a compound annual growth rate of ten per cent. The nation's logistics and freight market has steadily grown primarily driven by increasing international trade and electronic commerce's quick and consistent growth throughout the region.

A number of disruptions for trade took place during the COVID-19 Pandemic due not only to trading restrictions but also the trade war between China and the United States as well as the implementation of a number of new trade policies across the globe (Dash, *et al.*, 2019). This will likely have a different outcome in the coming years with trade treaty changes as well as the United States holding a new administration and the Asian Pacific region signing a new Comprehensive Regional Economic Partnership trade policy. This is likely to have a positive impact on the industry of logistics around the world, including the UAE. The nation, akin to its Gulf contemporaries, has faced a great deal of economic harm with its oil revenues falling well below expected in 2020 and its non-oil sectors also being impacted by global restrictions on movement, trade, tourism, etc.

The strategic location of Dubai between both Europe and Asia facilitates connections between the West and the East, thereby offering the Emirate with optimum conditions for trade. In order to facilitate the market of electronic commerce and trade, the Emirate has enacted initiatives for developing its technology and infrastructure with the goal being that of implementing an excellent infrastructure of logistics alongside an integrated system of transport (Dash, *et al.*, 2019). Research on the matter shows that the nation's sector of logistics is likely to contribute eight per cent to the economy of the nation, a five per cent increase from its prior rate (Cioffi, *et al.,* 2020). In spite of the economic headwinds that swirl across the Gulf as well as the economic conditions of recent years, the sector of logistics continues to remain one of fast paced development and progress. In fact, this sector has regularly outperformed a number of other important industries and is currently considered as one of the most significant enablers of the nation's efforts of economic diversification (Cioffi, *et al.*, 2020).

1.3.Research questions

In this regard, the following research questions will guide the work:

- What are the supply chain-based trends of automation with regard to machine learning and artificial intelligence?
- What type of supply chain outcomes can these technologies achieve?
- What level of these technologies can lead to such outcomes?

1.4. Research aim

By utilizing these questions as a point of starting, the author will focus on conducting a systematic review of academic literature alongside a bibliometric evaluation of it so as to assess artificial intelligence and machine learning in the supply chain context. Particularly, a descriptive analysis will be conducted to answer these questions, the findings of which practitioners as well as scholars can utilize as a reference for tracking this field's evolution as well as for envisioning the future of machine learning and artificial intelligence in supply chains. In the literature, there is no systematic artificial intelligence and machine learning application examination, especially with regard to the chain of supply process from a process viewpoint. Thus, an exploration of contemporary academia is appropriate for the study to contribute to filling existing literature gaps.

1.5.Research objectives

The research objectives of the current work include the following:

- Investigate the supply chain-based trends of automation with regard to machine learning and artificial intelligence
- Evaluate the type of supply chain outcomes can these technologies achieve
- Recommend the technologies that can lead to successful improvements in contemporary supply chains

1.6.Research process

The current work took on a quantitative focus with the author conducting a survey questionnaire for the purposes of data collection. This allowed the author to amass a suitable amount of data from a large enough sample size for the possibility of generalization. In this sense, the current study focuses on the link and relationship between variables such as automation, machine learning, artificial intelligence, and supply chain efficiency. The findings of this survey are segmented and arranged according to previously established themes.

1.7.Dissertation structure

The structure of the current work is segmented into five chapters which include the introduction for the current work, research background, and overall research aim. The second chapter then involves a detailed review of the literature on the matter ranging from artificial intelligence to machine learning with the third chapter touching on the methodology utilized for the current work. The fourth chapter then involves a short discussion and illustration of the findings of the current study with the five involving the drawing of conclusions, suggestion of recommendations based on the findings of the current work, as well as a brief overview of the limitations of the current study and possible future directions for further research efforts.

CHAPTER TWO: REVIEW OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

2.0. Introduction

This chapter introduces the relevant literature that provides the basis for this study. The literature includes detailed explanation of Artificial Intelligence and Design, Machine Learning and other key identified issues. The chapter ends with the summary of the literature.

2.1. Artificial intelligence and design

When Herbert A. Simon began his research on design, while still providing services for the RAND Project (Research and Development), in the United States, in the post-World War II period, he certainly did not imagine all the developments that this would entail. Artificial Intelligence and design are increasingly present in our lives, whether in geolocation applications, purchase recommendations on e-commerce sites and also in music, especially on streaming platforms. According to the text Revisiting Herbert Simon's "Science of Design", Simon's ideas form a theoretical basis that seeks to give a scientific character to the subject of design, and which aims to unify the social sciences with problem-solving models. In other words, design within science can be studied as a process that leads to a line of thought for solving problems within social research and in various sectors, including the Logistics Industry (Hartley & Sawaya, 2019).

Likewise, Woschank, Rauch & Zsifkovits (2020) defend the idea that it is possible to apply scientific methods in social research through conventional processes such as observation, research in laboratories and the use of mathematics and statistics. Based on the positions of Hartley & Sawaya (2019), Woschank, Rauch & Zsifkovits (2020) concluded that social research should have the same technical and investigative content as traditional scientific research, and design could also be studied on the basis of heavy research. Simon had went on to deeply study decision-making processes and how design could influence these processes. In his experience at RAND (Research and Development), when he worked on the development of solutions for the war industry, in the post-World War II period, Simon developed a work with problem solving and computing processes that was fundamental for research in Artificial Intelligence (Priore, et al., 2019). For him, human intelligence could be described by formulas and logical rules. In other words, through computational models it would be possible to create a decision system based on means-end analyses, such as human heuristics. At first, as a solution to the decision-making process for the armed forces, such as agenda control, for example (Hartley & Sawaya, 2019).

But AI tries to go beyond the understanding of human intelligence as it tries to replace it entirely with the construction of intelligent artifacts. The main definitions of artificial intelligence originate from this focus on intelligent machine engineering, which formally began in the 1950s, in parallel with the development of the first computers, and motivated by the thinking machine hypothesis of Turing (Sharma, *et al.*, 2020). The original and still current definition was coined by John McCarthy as “the science and engineering of producing intelligent machines” in the preparatory paper for what is considered to be the first conference on artificial intelligence, the “Dartmouth Summer Research Project on Artificial Intelligence”, held in 1956 (Toorajipour, *et al.*, 2021).

The Stanford Philosophy Encyclopedia proposes a similar definition, as being the “field dedicated to building artificial animals and people, or that resemble them”. Other definitions are related to the capabilities of an artificial intelligence. Priore, et al. (2019), for example, consider AI the intelligent behavior of artifacts, which involves the abilities of perception, reasoning, learning, communication and action. In psychology and cognitive science, AI is defined in the opposite direction as a discipline that aims to understand intelligent beings. This perspective has been present since Dartmouth, especially with Herbert Simon, mentioned above.

Around the unifying idea of building or reproducing an intelligent agent, perhaps the most common classification of AI is between weak and strong intelligence. "Strong" AI refers to creating conscious machines that can think for themselves or that have a mind of their own. “Weak” AI seeks to create machines that process information that appear to have the same mental repertoire as humans or that behave intelligently. In strong AI, the agent is the machine itself; in weak AI, humans always remain agents (Priore, *et al.*, 2019). This distinction is clear in the definition proposed by Syam & Sharma (2018), in which AI is a “set of calculations that make it possible to assist users to perceive, reason and act, and which may or may not be under the control of a machine” (i.e., computers or robotic systems).

AI can also be characterized by the two main approaches that grew out of the Dartmouth conference and which can be characterized as top-down and bottom-up approaches. In the first, AI depends on the development of deductive systems following the logistic and symbolic thesis, developed, among others, by Allen Newell and Herbert Simon (Radanliev, *et al.*, 2020). The central hypothesis involves the processing of structured symbols, in which a set of rules is applied, generating new structures. Symbols are representations of concepts or objects that are processed using logic.

In the second approach, AI is achieved from inductive processes, based on probability. This approach was developed mainly in the connectionist current (in the sense of the connection between neurons) of neurocomputing research. The bottom-up approach can be considered sub-symbolic, but not logistic. Considers intelligence as emergent and grounded in the data in the environment (Paschek, Luminosu & Draghici, 2017). Two sub approaches can be identified here, one of them purely probabilistic and the other connectionist. An example of this second is the neural networks that are interested in the ability to learn inspired by biological models, trying to mimic what we find at the cellular level (Beerbaum, 2021). The basic premise is that intelligent behavior derives from connections between us, called neurons in analogy to the natural system. The first algorithms of this type appeared in the 1940s-50s (Beerbaum, 2021).

Some AI historians identify periods of development that would correspond to “summers” and “winters”, that is, moments of euphoria and success, followed by others of difficulties and disappointments. The years following the Dartmouth conference, until the late 1970s, were years of excitement and expectations. During this period, although the first AI movements were made in connectionism and neural networks, AI based on symbolic systems prevailed, and it was the specialist systems that managed to stand out. This movement can be illustrated by the successes of Newell and Simon with the General Problem Solver (Wellers, Elliott & Noga, 2017).

In the 1970s, the failed attempt to deal with more complex problems, beyond the illusion that more and more computational power could be counted on and that this would be enough to solve them, brought AI back to reality. The following period consolidated the expansion of expert systems, but it also saw a rebirth of hope in neural networks (Wellers, Elliott & Noga, 2017). In the late 1980s, broken promises led to a new winter, the longest in the AI, which lasted until the end of the first decade of the 21st century. Research with connectionist models was resumed in the 2010s, and, based on computational progress, it is the protagonist of the new summer we are currently experiencing.

From the perspective of building intelligent artifacts or those trying to reproduce what the human mind can do, operationalization is usually based on the application of intelligence tests, with the Turing Test being the most important test of mental ability besides games such as chess and GO. Since then, the results of these developments are visible in several fields. In addition to playing GO or chess better than humans, there are already intelligent systems capable of driving autonomous vehicles, of extracting patterns from images and videos, from recognizing speech and writing and translating texts and audios, planning and organizing agendas, or even detecting fraud, identifying unwanted messages (SPAM), and carrying out logistical planning. In addition, there are specific applications to facilitate court decisions, predict the effects of climate change and possible mitigation actions, identify diseases and propose tailored education programs.

Despite this immense progress, the prospect of building an intelligence close to human seems still far away. One example is the poor performance of these systems in tests that are regularly used to test human intelligence, such as school tests. Dhamija & Bag (2020) describe one of these cases and attributes the machines' difficulty in getting good grades to the complexity of simultaneously dealing with graphics, texts and the general context of the issues. A good performance in a test like these is a much more complex task than chess or Go games and is perhaps a more appropriate benchmark for evaluating the performance of intelligent machines. The attempt to create artificial "scientists" also entered the agenda, but there are still important limitations.

2.1.1. Application of AI in value creation

Demand planning/forecasting that is based on computerized evaluations is not something that is new. This method is founded in a number of algorithms that aim to take several sets of data such as manufacturing data, ordering pattern, data of the product's life cycle, shipment data, and so on over a period of time to make a forecast. Contrasting this, systems that are enabled by artificial intelligence understand the most suitable combination of data sets and algorithms that have to be considered and lead to an accurate prediction. Furthermore, artificial intelligence has been aiding businesses in:

1. Attaining one hundred per cent accurate forecasts and projections of the demands that customers have
2. Helping businesses optimize their research and development to increase manufacturing at a lower cost whilst maintaining quality
3. Aiding businesses in their marketing efforts (designing marketing communication, setting pricing, estimating demographics, and identifying customers)
4. Offering customers with an improved experience

These four value creation areas are significant for attaining an advantage over one's competitors.

AI helps in the production

Artificial intelligence has played an important part in production due to the fact that it leads to improved process and asset optimization, improved team designs, the prevention of downtime for the purposes of maintenance, and improvements in reliability and quality. It has been due to artificial intelligence that the process of automation has been able to be furthered by great leaps in the last few years. One of the advanced branches of artificial intelligence includes robotics – something that plays an important part in production (Shah, *et al.*, 2020). Technology developments such as semantic segmentation and object recognition have changed the manner in which robots behave, particular with regard to the manner in which they identify the characteristics of the objects and materials that they interact with. New robots equipped with cameras and advanced artificial intelligence are being trained on how to recognize shelf spaces that are empty thereby leading to drastic changes in the manner in which inventory and storage management systems are implemented and processed (Shah, *et al.*, 2020).

Deep learning has also utilized in order to recognize the position and characteristics of an object. This allows robots to handle objects without the needing the objects to have predefined, fixed positions. One of the few retailers to use artificial intelligence platforms in their warehouses is Ocado, a United Kingdom-based supermarket, wherein robots are used to steer several thousands of bins comprised of products over conveyor belt mazes and deliver them to human workers in a timely manner (Hanga & Kovalchuk, 2019). In a similar manner, several other robots in this warehouse focus on whisking bags to delivery vehicles in which drivers are provided with appropriate guidance to their destination based on weather and traffic conditions (Priore, *et al.*, 2019). Robots enhanced by artificial intelligence in the field of logistics are also capable of integrating movement routine disturbances by means of dynamic learning engines. This ability helps in allowing for improved process robustness and precision (Felstead, 2019). Furthermore, collaborative robots, two or more robots working together, end up increasing productivity by almost twenty per cent (Hanga & Kovalchuk, 2019).

A good example of the manner in which artificial intelligence aids in production would be the production process of semiconductor chips that are enabled by artificial intelligence. The time taken from the initial processing of a chip's design and architecture to the final product can take up to several weeks and include several processes of intermediate quality-testing. The cost of testing as well as yield loss in the production of semiconductors comprises nearly thirty per cent of the overall cost of production. Manufacturers of semiconductors have started using artificial intelligence engines in order to recognize yield loss root causes that can be evaded by changes in the process of production. In order to improve on them, a number of applications are being designed in the current day to adjust and monitor subprocesses (Nayal, *et al.*, 2021).

Artificial intelligence methods aid in not only estimating the best conditions for a process or operation but also in reducing manufacturing defects. In a similar manner, businesses that are asset intense, wherein there is a minimal amount of downtime and the running systems are complex ones, artificial intelligence acts as the most optimum solution. Businesses in the field of utility employ artificial intelligence for the purposes of maintaining their facilities and networks. The use of hardware, drone, and sensor data can aid applications of machine learning in ensuring that operations are conducted in a way that avoids asset decommissioning whilst allowing the business to conduct remote maintenance and inspections (Hassija, *et al.*, 2020). One company in the field of power distribution in Europe has been able to use artificial intelligence to decrease its cash cost with artificial intelligence allowing it to conduct preventive maintenance (Nayal, *et al.*, 2021).

AI helps in the delivery

In recent years, there has been a push toward focusing on the experience of the user with many a company focusing on convenience and personalized experiences. Modern day businesses, due to the immense amount of competition that they face, focus on ensuring that every customer feels welcome and special – something that has proven time and time again to be a challenge (Priore, *et al.,* 2019). Prior to the modern day, such services and such a focus was specialized for lucrative customers given the expense and challenge that such an approach accompanies. Artificial intelligence, similar to machine learning and computer vision, has changed this dynamic entirely. An example of this would be when a regular shopper at a supermarket may place a given item into their cart, sensors and cameras would be able to rely such information to an artificial intelligence application, which would be able to understand which items are popular and in demand thereby replenishing inventory accordingly. Similarly, should the cart accompany a video screen then the system therein would be able to suggest similar items or complimentary ones to the customer based on their purchase behavior (Hassija, *et al.*, 2020).

Conversely, another example would hold how an athlete would be able to download an application from their preferred brand – one that would observe their observe their activity and recommend activities as well as products tailored to them in particular (Felstead, 2019). Amazon has built a number of stores in America that offer customers the ability to take food items off of shelves and leave the store without the need to pay at a kiosk (Schniederjans, Curado & Khalajhedayati, 2020). These stores, called Amazon Go, depend on tracking the patterns of shoppers by means of computer vision with the shopper being identified at the entrance and the items they leave with being associated with them alone.

Similarly, deliver through drones has also become a modern day reality with Amazon being able to cut traffic and deliver items directly to customers; Google partnering with food restaurants such as Chipotle to deliver meals; and Flirtey partnering with Dominos to commercially deliver pizzas (Hassija, *et al.*, 2020). Additionally, this has not been limited to the Western world alone as African governmental agencies, Zipline, and UPS had partnered to coordinate emergency blood deliveries in Rwanda (Hellingrath & Lechtenberg, 2019). Currently, Amazon regularly gathers drone data during deliveries in order to be able to estimate future purchases. In this sense, artificial intelligence is able to offer operation management tools to numerous types of businesses from logistics to manufacturing, from education to healthcare (Hellingrath & Lechtenberg, 2019).

AI helps to forecast demand and optimization

Artificial intelligence can be used effectively to forecast and project possible demand increases and decreases as most companies are also keen on ensuring that their demand and supply are balanced. Thus, an optimized forecast is required for the manufacturing and supply chain of most companies. As artificial intelligence is able to predict, analyze, and process data, it can offer reliable and accurate demand forecasts that help companies optimize their process of sourcing with regard to their order processing and purchases thus decreasing the expenses linked with administration, supply chain and warehousing, transportation, and so on. Additionally, as artificial intelligence is able to distinguish patterns and trends, it is able to construct improved strategies for manufacturing and retailing. An example of this would be how companies can use this instrument in a number of ways including the stocking of certain products that are popular thereby reducing waste as well as improving inventory optimization.

In a similar manner, attaining accurate trends of sales allows companies to ensure that they are able to restock on popular items easily. Such forecasts of demand are accurate to the point that they ensure a lack thereof product unavailability. According to Hellingrath & Lechtenberg (2019), platforms such as DeepMind by Google are able to predict suitable variations of supply and demand in an accurate manner that considers variables such as exogenous, weather-related inputs. Approaches of machine learning incorporate historic sales data and supply chain setup whilst depending on data that is nearly real-time concerning variables such as local weather, prices, and marketing campaigns (Hellingrath & Lechtenberg, 2019). An online retailer in Germany, Otto, was able to decrease ninety per cent of its inventory by utilizing such applications.

The artificial intelligence forecasts are reliable to the point that Otto, in expanding its inventory, is able to anticipate orders without depending on intervention from humans (Hofmann, *et al.*, 2019). Artificial intelligence has also been utilized in departments of research and development to be able to quickly evaluate whether a given design or product will fail or succeed in the market as well as the reasons for this. Most importantly, it offers an efficient overall design for transportation as well given that superfluous waste can be eliminated during the design process thereby reducing the weight and volume of the product.

2.2. Machine learning

The theory addressed in this chapter is based on Sebastian Raschka's book "Python Machine Learning". Machine learning is a side area in artificial intelligence that involves the development of self-learning algorithms (Hofmann, *et al.*, 2019). The algorithms convert data into knowledge that is used to find patterns in data structures and make predictions about future events. There are three variants of machine learning which are referred to as Supervised Learning, Unsupervised Learning and Reinforcement Learning.

2.2.1. Supervised learning

Supervised Learning uses algorithms to teach models to predict class affiliations. The classes are sets of objects with similar characteristics, which can be, for example, flower species, grades or music genres. The models use assigned data content to predict class affiliation on objects they do not know or objects that are expected to be added (Evtodieva, *et al.*, 2020). Through observations of historical data, the algorithms use the content of the known classes to find patterns for what is typical of a particular class. The pattern is then used to teach prediction rules to the models. The rules can be taught using different methods, where classification and regression analysis are the most common. Classification teaches the model to predict class affiliations on discrete values that are received irregularly. Regression analysis teaches the model a function that continuously outputs a value that corresponds to a graded class such as test results. As the content of the calendars cannot be graded, only the classification method was used in this work. Classifying algorithms have different approaches to achieve its predictive ability (Sarker, 2021). Some of the most basic algorithms are Perceptron, Adaptive Linear Neuron, Logistic Regression and K-nearest Neighbors (Evtodieva, *et al.*, 2020).

2.2.2. Perceptron

The algorithm Perceptron's structure consists of an activation function, a net input, weight coefficients w and input data x (Gray-Hawkins & Lăzăroiu, 2020). The weight coefficients are factors that are multiplied by input data, which creates a vector that points to predicted class affiliations. The vector is interpreted by summing its values in the model's net input. The sum is received by an activation function consisting of a unit step with a predefined threshold value. The sum is compared with the threshold value, which then gives a positive or negative value. The published value is then interpreted as a class affiliation (Baryannis, *et al.*, 2019).

The values of the weight coefficients are determined during the learning of the algorithm using the Perceptron Learning Rule. The algorithm uses training data that contains known classes. The algorithm then performs predictions on the classes in training data. If a prediction is not correct, the weight coefficients are updated. The update continues until the predictions agree with the entire training data. This is only possible if the classes are linearly separable (Baryannis, *et al.*, 2019). The fact that the contents of the calendars would be linearly separable means in practice that the available and recorded events of each weekday would consistently take place at the same times in the calendar in question, i.e., that it has a fixed schedule. If the trend were to be broken, the algorithm would not be useful as it cannot determine weight coefficients (Baryannis, *et al.*, 2019). The schedules of the provided calendars were not established, which meant that the algorithm was not used in the work.

2.2.3. Adaptive linear neuron (AdaLiNe)

AdaLiNe is an algorithm based on Perceptron. The difference between the algorithms is that AdaLiNe has a linear activation function and a quantizer. The quantizer consists of a unit step that interprets the value of net input to predicted classes, however, it has no effect on the learning of the algorithm. Instead, the linear activation function is used to teach the weight coefficients of the algorithm by generating a so-called cost function of all prediction errors that occur during learning (Gray-Hawkins & Lăzăroiu, 2020).

A cost function is used to map when the algorithm performs prediction errors during its learning. Based on the weight coefficients of the algorithm, the function gives a value, a so-called cost that is negative for the algorithm's performance. In order for the algorithm's performance to be maximized, the cost needs to be minimized to optimize its weight coefficients (Baryannis, Dani & Antoniou, 2019). A common method to minimize the cost is to use the gradient descent algorithm that iterates against the cost function gradient until a global minimum is reached.

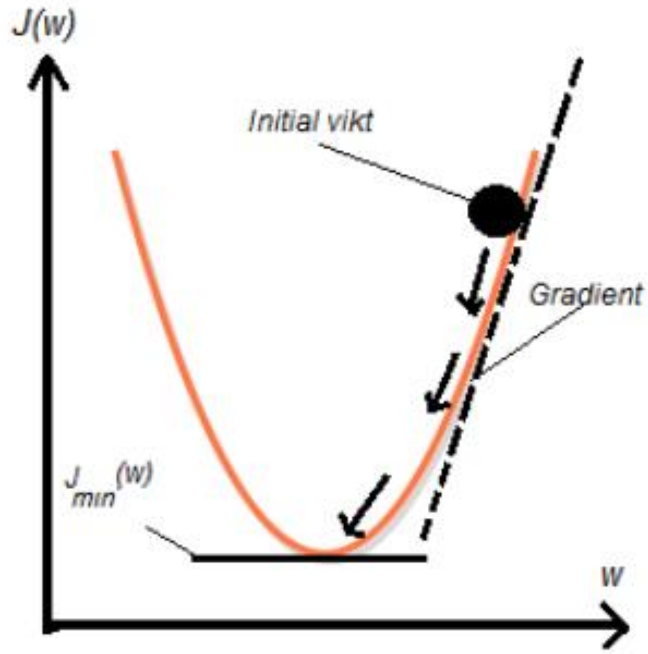

Figure: Illustrates how Gradient descent iterates towards the gradient until it reaches an extreme point. The cost is denoted as J and weight coefficients as w.

The calendars are dominated by booked events, which would issue a type of prediction. Adjusting the threshold value would be difficult as the value of the net input would be set relative to training data. Developing a method for this would cause problems as a relative threshold value would be difficult to find because there is no corresponding value in the calendars (Felstead, 2019). This meant that AdaLiNe was not used in the work.

2.2.3.1. Logistic regression

Logistic Regression is an algorithm based on AdaLiNe. The difference is that the activation function of the algorithm has a sigmoid-shaped function, which makes it possible to calculate the probability that a prediction belongs to a specific class. Based on calculated probabilities, the algorithm's learning and predictions are performed (Schniederjans, Curado & Khalajhedayati, 2020).

The sigmoid-shaped activation function uses the value input output value to calculate the probability that the prediction belongs to a certain class. The purpose of the probability is to indicate the reliability of the prediction. The calculated probability is used to update weighting coefficients during learning and predict class affiliations. In prediction, a quantizer is used to determine which class a prediction belongs to by comparing the calculated probability with a predefined threshold value. In learning, the optimization of the weighting coefficients is based on the probability that the algorithm's prediction of a class is correct (Gray-Hawkins & Lăzăroiu, 2020). The inverse of the probability is interpreted as a cost function that can optimize the weight coefficients according to the gradient descent algorithm. As the algorithm calculates a probability, the threshold value of the quantizer can be set based on the proportion of free time that is in the training data. This means that predictions can then give a positive outcome despite the fact that training data is strongly dominated by a class, which could give valuable results in the work (Baryannis, *et al.*, 2019).

2.2.4. K-nearest neighbors (KNN)

KNN is a predictive algorithm called lazy learner because it memorizes training data instead of learning a function that differentiates classes. The algorithm can predict an object's class affiliation by looking at objects in training data that have similar data content, so-called neighbor. The neighbors are found using a distance metric where a predetermined number of neighbors (k) is used to determine which class most closely resembles the object (Woschank, Rauch & Zsifkovits, 2020). The nearest neighbors each correspond to the voice of the object's class affiliation. The class with the most votes then becomes the prediction of the algorithm.

2.2.5. Unsupervised learning

Unsupervised Learning handles data that does not have class markers. By exploring the structure of the entire data set, patterns can be found in the data structure, which means that extracts of meaningful information can be retrieved. Cluster analysis is a pattern recognition analysis technique that organizes data sets of information into clusters without having prior knowledge of group affiliations. The technology is mainly used to structure information and obtain meaningful relationships between data. Each cluster that may be added during the analysis defines a group of objects with similar content. As the algorithms would find patterns when times were available, K-means and DBSCAN were assumed to be relevant for their clustering properties (Woschank, Rauch & Zsifkovits, 2020).

2.2.5.1. K-means algorithm

K-means is a cluster analysis algorithm for finding similarities between objects in a data set, where K refers to the number of divided clusters. Based on the similarities of the objects, the algorithm divides the objects into clusters to find patterns in the data set. During subdivision, the algorithm randomly selects a certain number of objects from the data set that are initially considered as the mean of each cluster. The object of the data set is associated with the nearest average value points to be initially divided into clusters, where the distance is calculated with a distance metric. After the division, a new mean value is calculated for each cluster based on the objects they contain (Hwang, 2018).

Based on the new mean values, a new association of the objects takes place, which leads to a new cluster division. Cluster redistributions continue until the algorithm reaches equilibrium or a redistribution limit has been reached. One problem with the algorithm was that all objects were assigned to a cluster (Ni, Xiao & Lim, 2019). This meant that different times could not be distinguished as a suitable time, which in turn led to the algorithm not being able to find the areas that had the most available times as the cluster division was not based on the number of objects in a certain area. This led to the algorithm not being used in the work.

2.2.6. Density-based spatial clustering of applications with noise (DBSCAN)

DBSCAN is a cluster analysis algorithm that is density based where each object is labeled before clustering. The objects are marked as core, boundary or noise points depending on which criterion it meets. The algorithm uses the following conditions to divide the objects:

- An object is considered a core point if a certain number of objects (k) occur within its radius ε, where ε is a predetermined radius.
- An object is considered a boundary point if the number of objects within its radius ε is less than k and the nearest core point is within radius ε.

- An object is considered a noise point if the object does not meet the criterion of being a core or boundary point.

After all objects have been selected, the algorithm creates clusters based on each core point. Core points are placed in the same cluster if they are closer than the distance ε. Then boundary points are associated with the nearest core point (Woschank, Rauch & Zsifkovits, 2020). This algorithm could show when most times have been available by allowing the clusters to specify these areas. This meant that the algorithm was used in the work (Woschank, Rauch & Zsifkovits, 2020).

2.2.7. Reinforcement learning

The purpose of Reinforcement Learning is to develop a system, a so-called agent, that gradually improves its performance. By interacting with the environment, the agent can learn to perform a series of actions that maximize a reward signal. The reward signal is based on the state of the environment which the agent interprets as positive or negative, which is seen as a measure of the agent's actions based on a reward function. As the agent tries to give a positive outcome to the reward function, the interaction develops continuously (Gray-Hawkins & Lăzăroiu, 2020). To consider with the reward function is that it does not function as training data for the prototype and it does not contradict training data that the model has been assigned. This type of machine learning could add valuable results to this work. In this case, the reward signal would be the calendar holder or the booker, which meant that tests could not be performed (Felstead, 2019). Therefore, the method was not addressed in this work, but it could be suitable for further work.

2.2.8. Demand forecasting with machine learning

Machine learning is part of AI where a computer learns from data by increasing its performance based on experience (Schniederjans, Curado & Khalajhedayati, 2020). Experience usually means that algorithms adapt to the data (Ni, D., Xiao, Z., & Lim, M. K. (2019). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, 1-20.). Woschank, Rauch & Zsifkovits (2020) say that it can be used for exploratory studies because with the help of machine learning one can find patterns within data that could not be detected with previously more traditional methods. This is possible due to the constant improvement of technology, especially in AI (Woschank, Rauch & Zsifkovits, 2020).

The use of machine learning in the problem area focuses mainly on trying to forecast demand within the supply chain. Gray-Hawkins & Lăzăroiu (2020) have studied whether machine learning algorithms such as neural networks, recurrent neural networks and support vector machines compare with traditional statistical methods such as moving average, naive forecasting trend. naive forecasting trend) and linear regression. Using two datasets, one from a simulated supply chain and the other from Canadian Foundries, it has been concluded that machine learning algorithms perform better. However, their forecasting accuracy is not statistically significantly better than the traditional models (Gray-Hawkins & Lăzăroiu, 2020). Reyes, Visich & Jaska (2020) has examined demand forecasts and compared statistical models: Holt Winters - triple exponential smoothing and seasonal autoregressive integrated moving average extended, machine learning algorithm: machine learning algorithm: machine learning algorithm: machine learning algorithm: machine learning algorithm: machine learning algorithm extreme gradient boosting and random forest and deep learning models: long-term short-term memory and multilayer perceptron.

The results have shown that when you take the mean value of the performance score (in this case the relative deviation of forecasting errors from the best model of each product) for all models, you get that the deep learning models are best followed by the statistical models and machine learning models. The in-depth learning models received performance scores of 81.9% while the statistical models received 80.8% (Reyes, Visich & Jaska, 2020). Deep learning is part of machine learning (Reyes, Visich & Jaska, 2020), the results do not indicate that the higher performance scores of the deep learning models are not significantly better. Vazquez-Noguerol, et al. (2021) suggest, however, that a consideration should be made as the deep learning models are more difficult to implement than the statistical models and require more computing power. When machine learning models have been used to forecast demand, namely algorithms such as neural networks and support vector machines, it has been shown that the errors in forecasting have decreased and thus also led to a smaller whiplash effect (Reyes, Visich & Jaska, 2020).

2.3. Key issues identified from the reviewed literature

As established from the literature reviewed, much of the literature on the matter seems to neglect a suitable focus on supply chain-based automation trends such as the integration of artificial intelligence and machine learning into the overall domain of supply chain. Additionally, the literature on the matter is predominantly Western with a clear deficiency in terms of any possible Eastern structures or efforts, especially those from the greater MENA or Gulf regions. Another key issue presented in the literature is that of the overt focus on artificial intelligence in terms of its design with scholars mostly debating the possible value creation role it plays whereas machine learning's focus is considerably more diversified and falls into numerous subcategories based on the type of machine learning at play. It was further found that:

- Herbert A. Simon is the creator of artificial intelligence design through his project with the US government after World War II, He created a work with problem solving and computing processes that was fundamental for research in Artificial Intelligence.
- The first definition of Artificial intelligence was coined by John McCarthy as "the science and engineering of producing intelligent machines".
- AI has been helping business for quite some time now in attaining accurate forecast, optimizing their research and development, aiding them in marketing efforts and creating a better experience for customers.
- The theory addressed in this chapter is based on Sebastian Raschka's book "Python Machine Learning". Machine learning is the process of converting data into knowledge to create prediction by an intelligent machine.
- Supervised Learning uses algorithms to teach models to predict class affiliations.
- The algorithm Perceptron's structure consists of an activation function, a net input, weight coefficients w and input data x. The weight coefficients are calculated on the basis of Perceptron Learning Rule,
- Unsupervised Learning handles data that does not have class markers. It uses cluster analysis to identify patterns.

Recently machine learning has been used in forecasting and the results showed that it has helped make forecasts more accurate and create less whiplash effect. Hence, we will be studying the trends of automation in supply chain with the use of artificial intelligence and machine learning and also their outcomes. As the author has analyzed the available technologies of artificial intelligence and machine learning, there seems to be a lack of knowledge regarding what is the minimum level of technologies required for complete automation of supply chain methods and hence, this paper will evaluate this aspect.

2.4. Chapter Summary

This chapter highlighted the main concepts of AI and ML. The chapter examined the evolution of both concepts and the many algorithms that have formed as part of machine learning. The chapter also appraised the uses of AI and ML in businesses, and specifically supply chain. The following gaps were identified from the review of literature and was related to the research objectives:

- Recently machine learning has been used in forecasting and the results showed that it has helped make forecasts more accurate and create less whiplash effect. Hence, the research examined the trends of automation in supply chain with the use of artificial intelligence and machine learning and also their outcomes. This is was covered by the following objective "***Investigate the supply chain-based trends of automation with regard to machine learning and artificial intelligence***".
- The researcher has appraised the available technologies of artificial intelligence and machine learning, there seems to be a lack of knowledge regarding what is the minimum level of technologies required for complete automation of supply chain methods and hence, this paper will evaluate this aspect. This was evaluated by the following two objectives: *"**Evaluate the type of supply chain outcomes can these technologies achieve" and "Recommend the technologies that can lead to successful improvements in contemporary supply chains**"*.

CHAPTER THREE: RESEARCH METHODOLOGY

3.0 Introduction

Considering the research classification model presented by Goddard & Melville (2004), which qualifies it in relation to two aspects, as to the ends and how many to the means, we can say that, in relation to the ends, this research is exploratory and descriptive. Exploratory, because there is no published research on the use of automation in the supply chain of companies in the UAE; descriptive because it aimed to describe the aspects related to the use of automation by supply chain organizations, as well as to quantify them. As for the means, the research was not in the field, as the author collected data through an online survey questionnaire that was distributed to individuals working supply chains of companies. The central objective defined for this study was to identify the applicability of automation technologies such as artificial intelligence and machine learning. Particularly, the author had focused on analyzing how automation through these two forms of technologies was being used in the modern supply chain of the UAE and the impact that these technologies have on not only the overall supply chains but the workers within them. Thus, the author made use of a quantitative survey questionnaire to effectively analyze the matter at hand.

According to Kothari (2004), “the methodology corresponds to a whole set of norms, principles and criteria, with a view to the selection and elaboration of techniques and research orientation”. The same idea is reinforced by Mohajan (2018), who state that “for each investigation, the methods must be chosen and used flexibly, depending on the objectives of the analysis model and the hypotheses”. Based on this methodological assumption, and taking into account the objective of this investigation, it was decided by the author that a quantitative methodological design would be preferable. For Kothari (2004), quantitative studies should follow an empirical approach that investigates a current phenomenon in its real context, when the boundaries between certain phenomena and its real context are not clearly evident, and in which many data sources are used. Its main objective is to explain the phenomenon. According to Snyder (2019), such studies aim to better understand the particularity of a given situation or process, being recommended when one intends to observe and describe in greater depth a given phenomenon.

Thus, due to the nature of this study, and with the purpose of reaching the outlined objective, it was decided as a methodology to make use of the quantitative methodology. Although a mixed methods approach would have been preferable, the author had lacked the time and resources needed to use such an approach and thus it was advised that further studies use such approaches. Here it should be also understood that the quantitative approach is much more helpful in this regard than a qualitative one as this approach allows for the gathering of a large enough sample population for the purposes of analysis that offer generalizable results and findings. Through such, the author was able to offer insight into the matter as well as explore it in detail. Conversely, a qualitative focus would have instead entailed the use of a smaller sample population and more exploration of the human impact of the technologies at hand thus reducing the generalizability of the findings and their statistical significance.

3.1. Justification of the method

Traditionally, research is associated with two major methodological paradigms: the quantitative and the qualitative (Snyder, 2019). Nevertheless, the literature on research methodology in social sciences has made this theoretical separation of boundaries that exists between these paradigms, the debate between positivists based on a perspective (quantitative) and the interpretive approach (qualitative), continues to trigger heated discussions, namely due to the subjectivity factor and respective limitation and control (Zangirolami-Raimundo, Echeimberg & Leone (2018). But according to Basias & Pollalis (2018), the question that should be asked is not so much about the greater or lesser scientificity of one methodology over another, but about the greater or lesser adequacy of each method to each specific object of study, and, if the investigation so requires, it can combine the use of two types of methods. Based on this reasoning, and based on the defined objective, there are thus two reasons to theoretically support the option of using, as a methodology for this study, the quantitative method. First, it is understood that the choice of the aforementioned methodology, followed in this investigation, meets the objective and type of study that configures this work. Because, according to Dodds & Hess (2020), quantitative studies imply the collection of quantifiable data that can be used to offer insight into a phenomenon, event, or experience in a manner that furthers the overall understanding of it.

In turn, according to Ørngreen & Levinsen (2017), Zangirolami-Raimundo, Echeimberg & Leone (2018), and Nayak & Singh (2021), the quantitative methodology is solid and offers advantages, since it has been a successful approach in other studies. Considering that reality is complex, we must use different methods to analyze this same reality. Thus, it is not that the quantitative methodology is more so better than the others rather that it is more suitable for the current study. Furthermore, the use of different methods can allow a better understanding of the phenomena and thus achieve deeper and more secure results from the study in question. In other words, taking into account the objective of the study, and the results that are intended to be achieved, this methodology allowed the author to guarantee the validity and reliability of the data even whilst others may have been helpful, should they have suited the aims and objectives of the current work. Ørngreen & Levinsen (2017) warn that, despite the advantages of combining the methods, this procedure presents some disadvantage and even a great challenge for the researcher, in trying to master the technique well. In this line of thought, there are authors, for example, Nayak & Singh (2021) who highlight the difficulties of using this method, claiming that the use of different research methods is also based on different assumptions, among others, about the social reality and nature of data collection.

3.2. Data Collection Tool

The main data collection tool used in this study was that of a survey questionnaire. In order to collect data related to the use of automation by supply chains in the UAE, the author chose to use a questionnaire with several questions that were electronically sent to select companies to respond. In this research instrument, the author mainly used closed ended questions (Basias & Pollalis, 2018); in general, the closed ended nature of the questions allowed the author to ensure that they could easily evaluate the matter at hand and effectively attain the responses of their participants in a manner that suited the analysis of them into numbers that were statistically significant.

3.3. Sample

The sample for this study was selected through convenience sampling and the total number of participants was 185. Originally, the author contacted 200 individuals to invite them for participation. However, only 185 provided completed surveys by the end of the study.

3.4. Survey

To increase the number of survey participants, the author included some companies that they had easy access to and, therefore, it would be easy to get answers to the questionnaire. The survey used was comprised of a total of five demographic questions and fourteen survey questions. The survey itself was based on a five-point Likert scale and was segmented into three individual sections.

3.5. Data analysis

The main software used for the analysis of data in this study was Microsoft Excel. The data was coded and then transcribed into Microsoft Excel where statistical tests were run.

3.6. Validation and verification

The study will be valid and verifiable as the population of the study is big and the results derived will be valid.

3.7. Chapter summary

This chapter explains the main methodology used in this study. The chapter explains how the study was carried out and what design was used. The chapter also gives information regarding the survey used as well the sampling technique. The chapter ends with providing information regarding data analysis and validity of the study.

CHAPTER FOUR: FINDINGS AND DISCUSSION

In order to achieve the objectives and research questions of the current study, the author had surveyed a total of one hundred participants. These participants were active parts of the greater supply chain process of the UAE and offered considerable insight into the matter at hand. In total, the survey sent to the participants was conducted through electronic means and was comprised of five demographic questions and fourteen individual survey questions that focused on varying aspects of the matter at hand. Thus, in order to effectively understand the results offered by the participants, it is important to understand their demographics. Particularly, as the below figure shows, the participants were individuals between the ages of twenty-eight and thirty-seven years. This showed that these were mainly young individuals who were likely to be aware of contemporary advance technologies and be highly literate in them given their close experience with them (Dash, *et al.*, 2019).

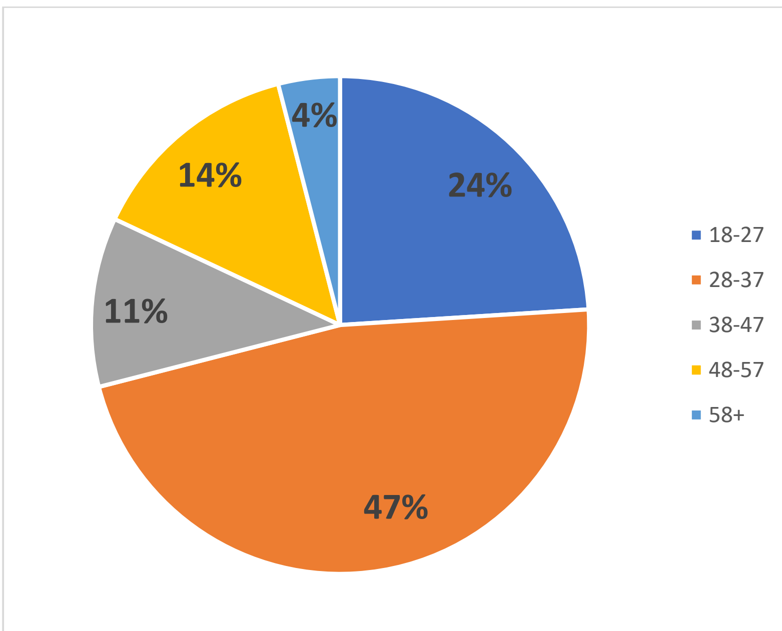

Figure 1: Age of participants

Particularly, here it can be seen that the majority, almost fifty per cent, of the participants were between the ages of twenty-eight and thirty-seven years. Conversely, whilst those between the ages of eighteen and twenty-seven years made up twenty-four per cent of the sample, those between the ages of thirty-eight and fifty-seven years comprised twenty-five per cent of the overall sample. This showed that the sample used was one comprised of relatively young individuals. Accordingly, in order to gauge the technological literacy of the participants, the survey had also asked them with regard to this matter. Herein, they were asked to offer responses ranging from that they were not very literate when it came to technology to that they were very literate when it came to technology. Although many of the respondents had stated that they were very literate when it came to technology, a surprising amount of the participants, totaling fifteen per cent had stated that they were somewhat literate when it came to technology. Specifically, seventy-two per cent of the respondents had stated that they were very technologically literate whereas thirteen per cent had stated that they were competently literate and fifteen per cent had stated that they were somewhat technologically literate. This showed that whilst the majority were well versed when it came to technology, the overall understanding of it and self-described competence in its use was low amid some of the respondents. This brings about interesting questions as to the impact that automation technologies can have on such individuals. However, inference leads the current author to believe that this difference in technological literacy may be due to the differing organizations that the participants would have worked in as well as their varying work experience.

The participants were then asked as to their gender to assess as to whether or not the opinions and perspectives that would be attained would be those of male participants or female ones as well as to evaluate possible gender-based discrepancies and differences in responses. In this regard, the majority of the participants were male individuals as seventy-six per cent of them were male individuals whereas the remaining were females. In comparing this result to that of their technological literacy, the author was able to find that the majority of the female respondents were highly technologically literate whereas male respondents were less likely to report higher technological literacy. This was also linked to their work experience as well as male respondents reported a higher average work experience than their female counterparts with males reporting that they had an average work experience of between six to twelve years whereas females reported smaller averages. Overall, the respondents' work experience is illustrated below in figure 2.

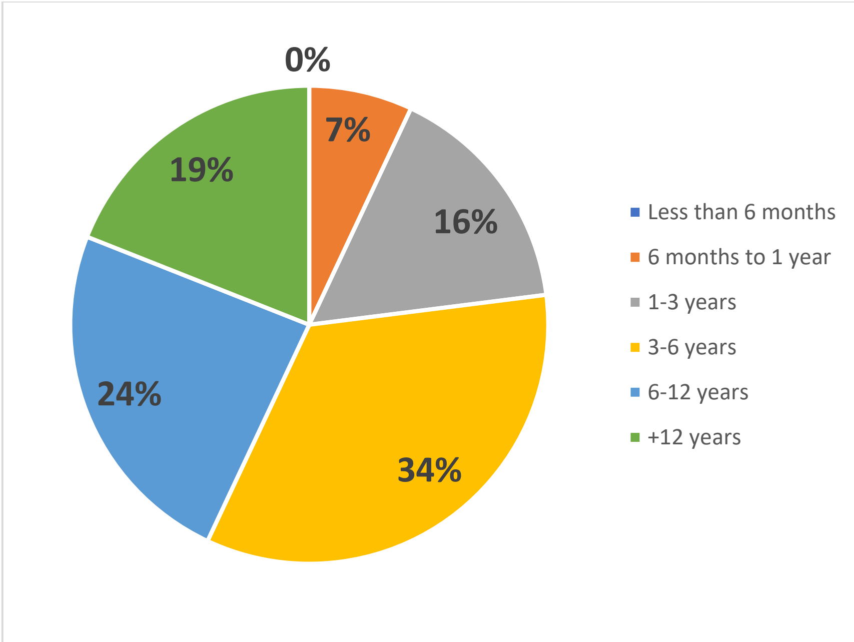

Figure 2: Work experience of participants

Herein, it can be seen that the majority held work experience for between three to six years whereas twenty-four per cent of the participants had work experience worth six to twelve years. Accordingly, the lower and upper thresholds were made up of similar percentages wherein nineteen per cent had more than twelve years of work experience and sixteen per cent had work experience ranging from one to three years. Conversely, no participant had less than six months of work experience and very few had between six months to a year of work experience. Lastly, the participants were asked with regard to their area of residence to assess the opinions and their prominence. Particularly, the majority had stated that they were either from Dubai or Sharjah with the remaining stating that they were from Abu Dhabi. In total, forty-two per cent were from Dubai, thirty-six per cent from Sharjah, sixteen per cent from Abu Dhabi, and the remaining from other emirates.

4.1. Trends in supply chain

Accordingly, the survey was made up of ten individual survey questions that evaluated the perception and opinions of the participants with regard to trends within the current supply chain process and how automation was impacting the supply chain in terms of efficiency. Herein, with regard to this subsection of the survey, the author was able to find a number of important findings. Particularly, the survey asked participants as to their agreement and disagreement with the question items listed. Firstly, they were confronted with the notion that automation had become an important and rising trend within the supply chain process. To this, the responses were mainly in agreement with the participants showing that automation, for them was overtaking the supply chain process and had become an important aspect of this industry. Research on the matter also shows that automation has increasingly become significant in much of the world with industries such as business logistics (Dash, et al., 2019). Following this, the participants were asked with regard to their companies' integration of machine learning. The responses of the participants are illustrated in the below figure with the question items ranging from full integration, to partial, to none at all.

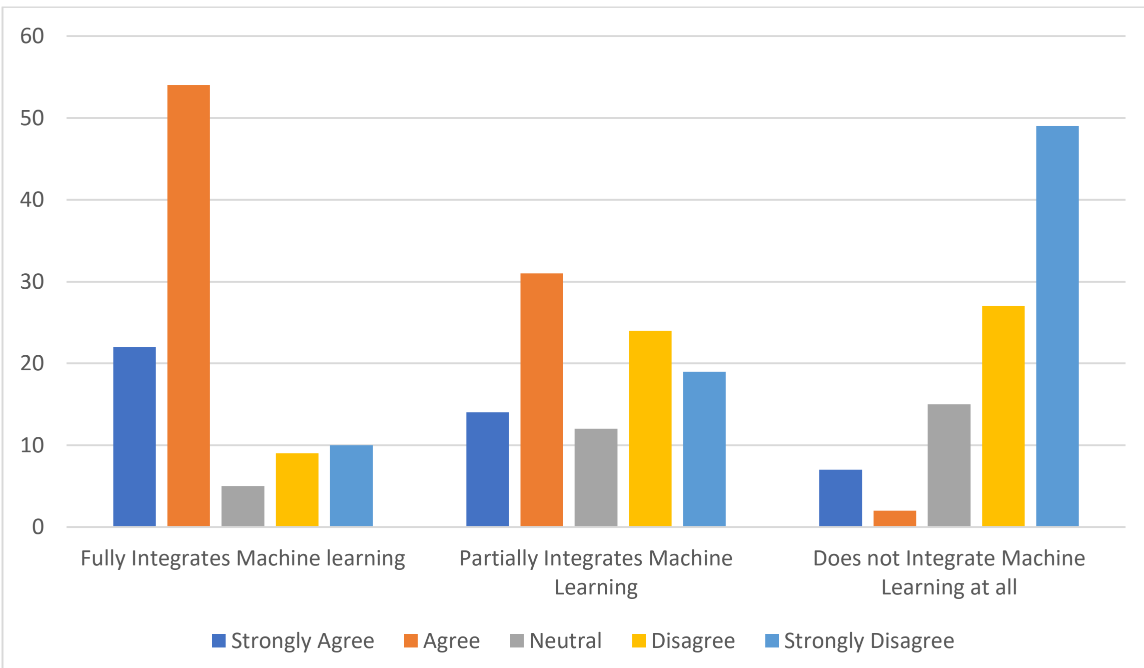

Figure 3: Integration of machine learning

Herein, Figure 3 shows that more than seventy per cent of the respondents' companies had integrated machine learning fully with similar opposite responses were received when the participants were confronted with the notion that their companies did not integrate machine learning at all. This further illustrates that machine learning and similar automations were being actively implemented in the supply chain. This also reflects the overall UAE's shift toward technological advancement and how similar trends are taking place around the world (Baryannis, Dani & Antoniou, 2019). Accordingly, it can also be seen here that a number of the participants showed that their organizations partially integrated machine learning as well with upwards of forty per cent partially integrating machine learning and more than thirty per cent showing that they did not integrate it partially. Lastly, more than ten per cent showed that their organizations did not integrate machine learning at all.

Accordingly, the participants were then asked as to whether or not their companies had automated processes through artificial intelligence software. This received less of an agreement from the participants than machine learning showing that artificial intelligence was less so used to automate processes. This may be due to the fact that implementing artificial intelligence in the supply chain is highly challenging (Woschank, Rauch & Zsifkovits, 2020) and, compared to machine learning, much more costly and less useful for supply chain management and operations. Conversely, research shows that machine learning is useful in improving the way in which inventory management takes place within the chain of supply as well as in improving warehouse management and communications between channels within the chain of supply (Ni, Xiao & Lim, 2019). This thus shows the responses of the participants align with their companies' needs as well as operations and the overall literature on the matter (Dash, et al., 2019; Hanga & Kovalchuk, 2019; Gray-Hawkins & Lăzăroiu, 2020).

The last question that was asked of participants under this theme of the survey was that of whether or not most of the supply chain process, in their perspective, had become dependent on automation to perform processes and duties. The participants responded to this with neutrality mostly showing that this was the case for some and not others. Particularly, this lack thereof a sufficient consensus may be due to the fact that the overall supply chain of most companies is one that is highly varied and differs from one company to the next thereby requiring differing amounts of automation, information technology, professional expertise, and so on. In total, forty-three per cent of the participants had collectively agreed that the supply chain process had become dependent on automation to perform its duties and processes whereas thirty-nine per cent had disagreed with this perspective. Additionally, the remaining eighteen per cent of the respondents stood neutral in this regard.

4.2. Application of artificial intelligence and machine learning

Accordingly, the second subsection within the survey then had focused on the application of automation technologies such as artificial intelligence and machine learning in the supply chain. Herein, participants were asked with regard to whether or not their companies had used these technologies to automate menial tasks and duties that did not require sufficient supervision. To this a mixed ranged of responses was received with twenty per cent leaning more toward agreement than disagreement. Particularly, whilst thirty per cent had collectively disagreed with this matter, fifty per cent had collectively agreed with it.

Following this, the participants were confronted with the notion that technologies had helped their companies in only automating those tasks that require supervision. Herein, a similar response range was seen as with the previous question item. However, a greater majority did lean toward neutrality with regard to this question item showing that automation through artificial intelligence and machine learning was not mainly used to automate those tasks that required supervision. This may have been due to the fact that such tasks are often challenging for individual humans to perform and thus automating them would entail a higher risk should the automation fail or make errors along the way. Furthermore, the participants showed that one or more individual would be continually needed to supervise these technologies' performance. These responses are shown below.

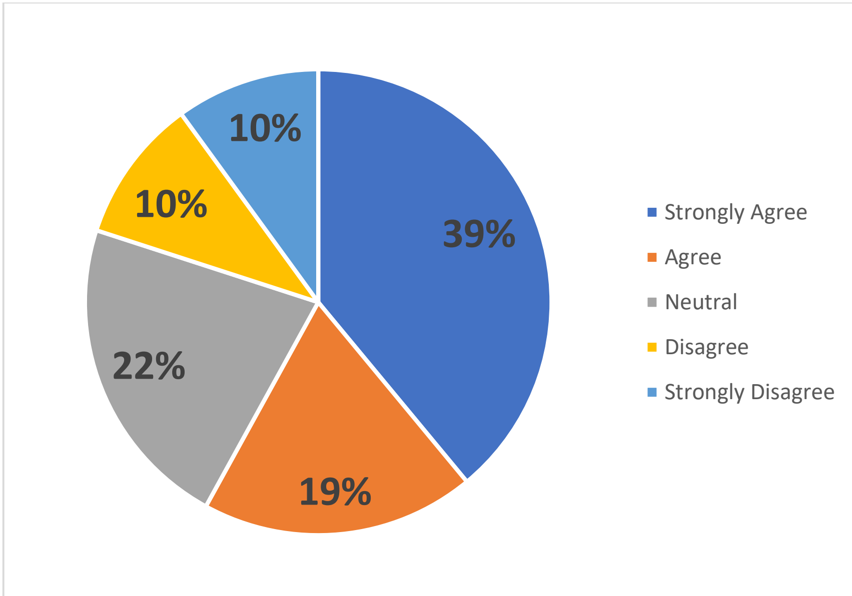

Figure 4: Percentage of participants who perceive that one or more individuals are required to supervise automation

The responses herein show that the participants' organizations focused on automating tasks but also ensuring that there were individual in charge of supervising said automation to ensure that no errors took place. Although automation itself is meant to eliminate the need for human effort, the use of human supervision over automated tasks – especially in busy industries and areas such as supply chain – is quite commonplace (Dhamija & Bag, 2020; Woschank, Rauch & Zsifkovits, 2020). However, the particular reason that the respondents' organizations had done this was unclear and thus requires further research to effectively understand it. Lastly, the participants were asked as to whether or not their companies had mainly used artificial intelligence and machine learning technologies to automate tasks such as inventory management – as prior responses also alluded to the use of these technologies in this regard and the literature on the matter also shows that this is quite commonplace in supply chains. In responding to this, the respondents had collectively agreed thus showing that this was the case, in corroborating with the literature on the matter. This illustrates that automation was mainly used to ensure that simple tasks that did not require supervision could be automated. In this sense, automation was used mainly to complement human workers and ensure that they could improve their performances and operations thus enhancing the overall supply chain through such automated technologies' integration.

4.3. Supply chain efficiencies

This was the last subsection under the survey and focused on attaining the perspectives of participants with regard to the efficiency brought on to their chain of supply through the integration of automation. Herein, the first question item had asked participants as to whether or not they had regarded their companies' chain of supply as being highly efficient. In responding to this, the majority, around seventy per cent, had collectively agreed thus showing that they had regarded their companies' chain of supply as being one that was highly efficient. Additionally, these were mostly individuals who had regarded the supply chain process itself as being highly dependent on automation in the modern day and their companies were mainly the ones that had fully integrated automation into their supply chains. The participants were also asked as to whether or not staff found it challenging to use such advanced technologies. To this, the majority had disagreed as shown below.

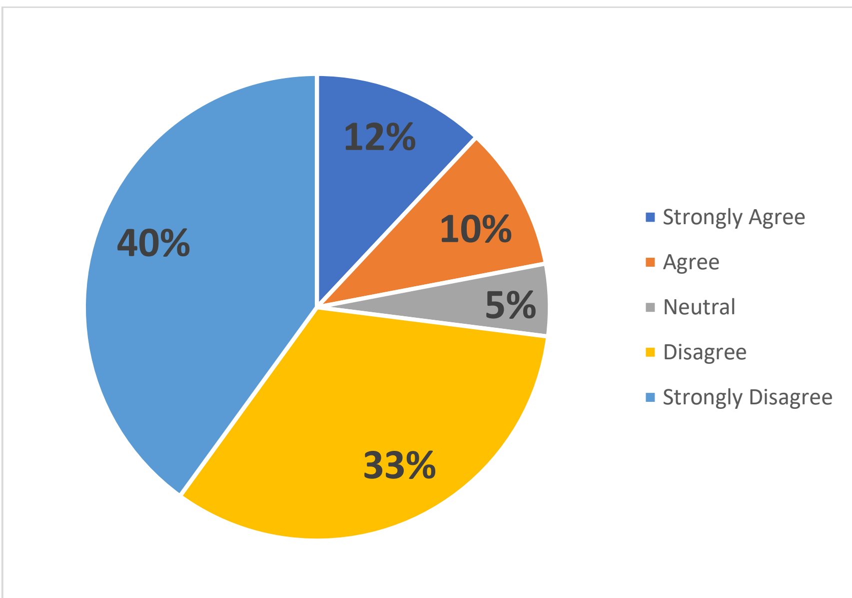

Figure 5: Percentage of participants who regard staff as finding it challenging to use automation technologies

Here it can be seen that more than seventy per cent of the respondents did not think that staff had found it challenging to use such technologies with only a handful of participants had agreed to this notion. This showed that these technologies were not challenging to use and that those working in the supply chain were well familiar or at least competent in using them. Then the participants were confronted with the notion that their supply chains had become more efficient by means of implementing these two types of technologies. Herein, the vast majority had collectively agreed showing that this was the case. Particularly, almost eighty per cent of the participants had stated this and showed that their supply chains were significantly improved as a result of such automation technologies. The inverse of this question item was then asked at the end of the survey to assess as to whether or not the participants' chain of supplies had become inefficient, in their opinion, through the implementation of automation technologies. This was not the case, however, as those that had agreed collectively with the second last question item had disagreed collectively with the last question item asked of them.

Chapter summary

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1. Introduction

5.2. Conclusions

The current work was conducted by means of a quantitative design with the author focusing on analyzing the perspectives and opinions of numerous individuals within the greater supply chain process and industry of the UAE to assess the impact and application of automation technologies such as artificial intelligence and machine learning. Throughout the course of the current study, the author was able to find a number of significant findings related to the matter at hand. Most particularly, the author was able to find that a number of significant trends are currently taking place in the chain of supply of the UAE. Particularly, the author was able to find that automation, particularly through machine learning has come to be highly prevalent in the chain of supply of the nation. However, artificial intelligence is significantly lacking overall. Particularly, this may be due to the fact that this technology itself is currently in its early years and still has several decades of development and advancement to it (Paschek, Luminosu & Draghici, 2017). In this sense, it is likely that the coming years will see several changes to take place for the supply chains of most companies in the nation. Additionally, many of those who were surveyed were mainly adult males who had held a significant amount of work experience that showed their place in the industry and showed that they were well versed in their opinions. The author was also able to find that most, if not all, members of staff in the supply chains in the UAE regard automation technologies such as artificial intelligence and machine learning to be free of any possible challenges and difficulties. Adding to this, with regard to the second research question of the study, the author was able to find that their results align with those present in the literature.

Particularly, they were able to find that the supply chain outcomes these technologies achieve are highly significant and can greatly improve the efficiencies of the organizations in which they are implemented. In doing so, automation technologies such as these can greatly enhance companies and improve their overall performance and output. Moreover, these automation technologies work hand-in-hand with human individual workers and thus improve the company rather than take the place of human workers. Lastly, with regard to the third research question at hand, the level of these technologies that can lead to such outcomes, the author was able to find that primarily those automation technologies are helpful that work alongside human workers and improve their performance as well as that of the company. The main type that was used by those surveyed were ones that did not require supervision from humans and still had human workers supervising their performance and output. Doing so allowed these companies to ensure that these technologies worked in tandem with their workers and that they did not make any possible errors in their performance or operations.

5.3. Recommendations

Through the current findings, the author is able to offer a number of recommendations to not only organizations within the greater chain of supply industry and process but also for policymakers and those in charge of implementing such automation technologies. First most, it is important for those within the supply chain to ensure that they are able to implement these technologies in such a manner that works alongside their individual employees and on levels such as inventory management and assessment. Doing so would ensure that these technologies aid workers in achieving their tasks and duties in a much more efficient and productive manner. As the literature on the matter and the findings of the study show that these technologies are likely to make errors along their processes should they not be supervised. Thus, it is also important to ensure that there is a sufficient team or handful of individuals in charge of supervising these technologies.

For policymakers, it is important to ensure that there are mechanisms in place to enable supply chains to be able to implement these new and advanced technologies and make sure that there is sufficient technological leeway and advancement in the nation for this. By enabling the furthering of such technologies and their widespread usage, policymakers would be able to ensure that the nation’s businesses can further their economic contributions and performance. Lastly, with regard to those implementing these technologies, it is recommended that they ensure that these technologies, even when replacing human workers, are able to be implemented in a manner that does not require continued supervision. However, if they are implemented in a manner that works alongside human workers, then it is important for those in charge of their implementation to account for the impact that they would have on the human workers as well as the supervision required for the technology itself. Doing so would greatly improve and help these organizations in enhancing their overall performance and efficiencies. Thus, it is important for those implementing such technologies to ensure that they account for such factors as well as evaluate the overall costs involved in implementing either machine learning or artificial intelligence.

5.3. Suggestions for Future Research

With regard to future literary efforts on the matter, the findings of the current work offer sufficient leeway and guidance. Particularly, it is suggested that further literary efforts on the matter evaluate the impact of artificial intelligence and machine learning separately to evaluate the costs as well as overall output that these technologies offer when compared to one another. By doing so, future academics would be able to improve the literature on the matter and make sure that they can effectively analyze the subject matter further. Particularly, the current author suggests that future research efforts focus on also comparing the supply chains within the nation to ones in other nations to assess the automation taking place as well as the impact of said automation. In order to effectively analyze the rate of automation occurring and its impact, future academics should focus on conducting either mixed methods research or qualitative research on the matter. This would aid them in gathering qualitative information or in gathering quantitative information that they can analyze alongside the qualitative data on the matter.

Most important, machine learning's significance and usage may be due to the fact that it is an affordable alternative when compared to the implementation of artificial intelligence. Additionally, given the fact that machine learning suits the supply chain process well, future academics should attempt to analyze which other forms of automation have been or are likely to be helpful in improving the efficiency of this process. Doing so would allow future academics to greatly improve the literature on the matter and offer insight into which technologies are helpful in improving the process's performance and productivity. Moreover, this would aid the overall understanding of the matter to make sure that practitioners are able to effectively analyze their operations and ensure that they can reduce downtime during the overall process.

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Survey

- **Age**
    - 18-27
    - 28-37
    - 38-47
    - 48-57
    - 58+
- **Technological Literacy**
    - Not much
    - Somewhat literate
    - Competently literate
    - Very literate
- **Gender**
    - Male
    - Female
- **Work Experience**
    - Less than 6 months
    - 6 months to 1 year
    - 1-3 years
    - 3-6 years
    - 6-12 years
    - +12 years
- **Area of Residence**
    - Dubai
    - Abu Dhabi
    - Sharjah
    - Other

S. No.	Question	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Trends in Supply Chain						
1.	Automation has become an important and rising trend in the supply chain process					
2.	Your company fully integrates machine learning in its processes					
3.	Your company partially integrates machine learning in its processes					
4.	Your company does not integrate machine learning in its processes					
5.	Your company automates processes through artificial intelligence software					

6.	Most of the supply chain process has become dependent on automation to perform its duties and processes					
Application of Artificial Intelligence and Machine Learning						
7.	Your company uses these technologies to automate menial tasks and duties that do not require supervision					
8.	These technologies help your company automate those tasks that do require supervision					
9.	One or more individual is continually tasked with supervising the performance of these technologies					
10.	Your company mainly uses these technologies to automate inventory management and similar tasks					
Supply Chain Efficiencies						
11.	Your company has a highly efficient supply chain					
12.	Staff find it challenging to use advanced technologies such as artificial intelligence and machine learning					
13.	Your supply chain has become more efficient through the use of artificial intelligence and machine learning					
14.	Your supply chain has become inefficient through the use of artificial intelligence and machine learning					